APPLICATIONS OF MODELS OF ACTIVITY BEHAVIOR FOR ACTIVITY BASED DEMAND FORECASTING

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1. INTRODUCTION

In the period of about two decades since the activity-based approach to travel demand analysis was proposed, extensive empirical results have been accumulated, methodologies for collecting data needed for activity-based analysis have been developed, models capturing various aspects of activity-travel behavior have been formulated, and model systems for demand forecasting are now being constructed. The activity-based approach remained largely within the domain of academic research until recently, when the limitations of the conventional, trip-based demand forecasting tools in the current planning contexts were widely recognized.[1] In fact the activity-based approach is the only approach that can offer coherent frameworks for policy analysis and demand forecasting with the wide range of travel demand management (TDM) and other policy measures that are being considered for improved mobility and reduced environmental impact.

Jones *et. al.* (1990) provide a comprehensive definition of activity analysis as: it is a "framework in which travel is analyzed as daily or multi-day patterns of behaviour, related to and derived from differences in life styles and activity participation among the population." The "emerging features" of activity analysis are identified (Jones *et. al.*, 1990) as:

- Treatment of travel as a demand derived from the desires, demand to participate in other, non-

[1] Kitamura (1988) attributed this inattention by the practitioners' community to the fact that the activity-based approach is not suited for the evaluation of capital-intensive, large-scale projects, but it is better suited for refined, often small-scale transportation policy measures. Unfortunately small-scale projects can rarely afford elaborate analysis. This is no longer the case, at least in the United States where the importance of refined transportation control measures is well recognized and efforts are being made to promote their implementation and to assess their potential effectiveness.

travel activities;

- Focus on sequences or patterns of behavior, not discrete trips;
- Analysis of households as the decision-making units;
- Examination of detailed timing and duration of activities and travel;
- Incorporation of spatial, temporal and inter-personal constraints;
- Recognition of interdependence of among events; and
- Use of household and person classification schemes based on differences in activity needs, commitments and constraints.

Many studies have been undertaken, placing different levels of emphasis on each of these points. Reviews of activity-based studies accumulated thus far can be found in Damm (1983); Jones (1983); Kitamura (1988); Jones *et. al.* (1990); Axhausen (1990); Axhausen and Gärling (1992); Gärling *et. al.* (1994); Jones (1995), and Kurani and Kitamura (1996).

The activity-based analysis is now entering the stage of producing practical tools for policy analysis and demand forecasting. The tools that are being developed may look quite different from the conventional, trip-based tools of travel demand analysis. Trip-based models typically determine the number of trips first, and then determine the attributes of these trips to produce demand forecasts. This, however, is not consistent with the way we behave. No one would think about how many trips to make when developing a plan for a day; rather, one would think about what she wants to or needs to do, where the activities can or need be engaged, and, only then, would think about how to visit these places. Importantly, how many trips will be made depends on how the visits to different places are sequenced and combined into trip chains. Trip-based approaches to travel demand forecasting thus rest on dubious behavioral ground.

Activity-based demand forecasting, then, should be based on a model of activity engagement, and then should forecast the number of trips and their attributes, given a set of activities to be pursued. Modeling activity engagement, however, is not at all a trivial task. Kurani and Kitamura (1996) note that

> "the paradigm [of activity-based analysis] has yet to develop or adopt a comprehensive theory of activity participation. ... Lacking such a theory ..., we are able to assess neither the motivations for choosing to participate in a given activity nor the decisions as to when and for how long to engage in a chosen activity. Chapin (1978) applied a simple theory based on Maslow's "hierarchy of needs" (Maslow, 1970) in his investigation of differences in activity patterns between different socio-economic groups of people. Tonn (1983a, 1983b) delineated a system of activity participation, but acknowledged he had to draw on an eclectic blend of psychological theories and maxims, none of which could be regarded as widely accepted. Bhat and Koppelman (1993) have proposed a framework of activity program generation, but this framework is not a direct link between activities and needs."

Presumably this is where the challenge in activity-based analysis lies. For example, Gärling and Garvill (1993) propose that investigation be made into how the activities performed are related to the

individual's goals.
This, however, is not to suggest that the activity-based approach is inept in providing useful planning information. In fact, the conceptual framework of the activity-based analysis offers features that facilitate coherent analysis of travel demand. While no widely accepted model of activity engagement has been in existence, "utility-maximizing" discrete choice models of activity engagement and statistical models of activity durations have served as critical components of micro-analytic models of activity-travel behavior. As is reviewed briefly in this paper and is treated more rigorously in Axhausen and Gärling (1992), Gärling *et. al.* (1994) and Kurani and Kitamura (1996), research is progressing at healthy rates in areas that support the construction of activity-based model systems of travel demand forecasting.

The forecasting models reviewed in this paper can be classified into two groups:

- structural equations model systems of measures of mobility and activity participation, and
- micro-simulation model systems of individuals' activity engagement and travel.

The structural equations model systems capture relationships among individual-level, macro-measures of mobility and activity participation (e.g., number of trips, total travel distance, total travel time and time allocated to each type of activity) and exogenous (explanatory) variables (which are typically person and household attributes, network variables, and land use information). In the sense that they do not explicitly model the behavioral mechanisms underlying activity participation and travel behavior, but merely trace salient statistical relationships among indicators of activity-travel behavior and explanatory variables, one may not consider them truly "activity-based." Yet they have proved to be effective tools in addressing a range of issues including that of induced travel demand.

The latter, micro-simulation approach includes modeling efforts that attempt to replicate the decision mechanisms underlying activity engagement and travel. Several model systems have so far been proposed. They each have unique focuses, e.g., memory structure, search processes, activity scheduling, adaptation, and time-space constraints. These models are by definition microscopic and require types of data that have not been used in traditional travel demand analysis (Axhausen, 1995, considers data needs for models of activity scheduling). Yet, prototypes exist that rely on information that is mostly available from local planning organizations.

Reviewed in this paper are samples of studies from these two groups, in which activity-based models have been applied to demand forecasting and policy analysis. The objectives of this review are to summarize the progress so far made in the application of activity-based models to demand forecasting, and to demonstrate the benefits this approach will offer when it is fully developed. In the next two sections, the limitations of the conventional trip-based models and the reasons why activity-based models should be used, are discussed. In Section 4, requirements for activity-based demand forecasting are discussed. Application examples of structural equations models and micro-simulation models of activity and travel are presented in Sections 5 and 6, respectively. Section 7 offers conclusions.

2. A CRITICAL REVIEW OF THE TRIP-BASED, FOUR-STEP MODELS OF TRAVEL DEMAND

In the Detroit Metropolitan Area Traffic Study (DMATS) which started in 1953, Weiner (1992) reports that "Much of the work was done by hand with the aid of tabulating machines for some of the calculations." Given the cost and speed of computation, and the software available for statistical analysis and data-base management, it is not surprising that the travel demand model systems developed in the 50s and 60s involved:

- aggregation of data to make the data-base manageable and to reduce computational requirements;
- simple models that do not require lengthy computation for the estimation of their parameters and preparation of forecasts; and
- parsimonious models that include only the most salient variables.

When tabulating machines are the only computational tools available, inverting a 5-by-5 matrix would not be a trivial task. Consequently linear regression models could include only a limited number of explanatory variables. Likewise, modal split models were zone-based and incorporate only a few, most obvious explanatory variables.

It should nonetheless be acknowledged that the simplifying assumptions adopted in the four-step procedure facilitated quantitative analysis of urban passenger travel demand, using home-interview survey results, land use inventory data, network models, census and other existing data, and computational capabilities that were available decades ago. When reviewing transportation planning models that are currently in use, however, one may notice that some are still bounded by the limitations in computer hardware and software that existed when the four-step procedure was being developed.

The development of the four-step procedure was motivated by the planning needs of the 50s and 60s when the expansion of transportation infrastructure was of primary concern. This is the period of the "suburban boom," whose four main foundations were: new road, zoning of land uses, government-guaranteed mortgages, and a baby boom (Hall, 1988). With the rapid suburbanization, what was needed was road networks that effectively connected the central city as the place of employment and suburbs as the place of residence. Commute trips to and from work were of primary concern when road networks were planned. Given these planning contexts, one would agree that the trip-based, four-step model system is a streamlined procedure which adequately served the planning needs of that time. Indeed it represents skillful simplifications to develop a practical tool to meet the planning challenges of the time.

The procedure, however, contains limitations, some of which were discussed extensively when disaggregate choice models were proposed in the 70s. Furthermore, significant changes took place since the 50s and 60s in demographic and socio-economic characteristics of households (e.g., more working women, small households and single-parents), urban forms (e.g., commercial developments in suburbs), industrial composition, distribution systems (e.g., shopping malls), and consequently in travel patterns. Planning emphases have shifted from infrastructure development to transportation systems management (TSM) to TDM. And energy and environment have emerged as new concerns of transportation planning. The trip-based, four-step procedure that was tailored to the planning needs of the 50s and 60s, just does not serve well in the current planning contexts.

The discussion in the rest of this section focuses on three major sources of problems that are most deleterious in the current transportation planning contexts: (i) lack of behavioral basis, (ii) lack of the time dimension, and (iii) trip-based model structure.[2]

Lack of Behavioral Basis: Attempting to represent demand by the serially linked four model components presents problems under certain conditions. Suppose parking pricing is implemented in a downtown area, prompting some travelers to choose suburban destinations. This change in trip attraction, however, would not at all be accounted for by the four-step procedure because trip attraction is determined in the trip generation phase, which is not sensitive to parking cost. Likewise, the impact of new highway segments on trip distribution would be under-estimated, while mode shift could be over-estimated, because of the typical insensitivity of trip generation/attraction models to accessibility. Issues of induced trips and suppressed demand are difficult to address within the structure of the four-step procedure. These problems arise because the four-step procedure does not represent the decision mechanisms underlying travel behavior. As noted earlier, people do not decide how many trips to make before deciding what to do, where to go, and how to get there.

Lack of Time Dimension: The fact that the four-step procedure does not incorporate the time-of-day dimension is curious since congestion — which has been the single most important concern of transportation planning — occurs with the concentration of demand in the same geographical area within the same time period. The absence of the time dimension necessitates the use of purely empirical, often dubious, procedures to determine hourly demand volume. It makes it difficult to thoroughly analyze peak spreading, assess impacts of congestion pricing, or predict the distribution of cold and hot starts.

Trip-Based: The four-step procedure treats each trip as an independent entity for analysis. This assumption, on which the structure of the four-step procedure hinges, leads to a number of serious limitations which stem from the fact that trips made by an individual are linked to each other and the decisions underlying the respective trips are all inter-related. For example, consider a home-based trip chain (a series of linked trips that starts and ends at the home base) that contains two or more stops. The four-step procedure would examine each trip separately and determine the best mode for it, leading to two major problems. Firstly the result may violate the modal continuity condition; mode choice for a trip with non-home origin is conditioned on the mode selected for the first, home-based trip. Secondly, the result ignores the behavioral fact that people plan ahead and

[2] The discussions in the remainder of this section are drawn from Kitamura *et. al.* (1995a) and partially expanded.

choose attributes of each trip (including mode, destinations, and departure time) while considering the entire trip chain, not each individual trip separately.

One of the possible consequences of these limitations is an over-prediction of mode shift.[3] The problem is compounded by the fact that the modal split phase of the four-step procedure, where disaggregate choice models are often incorporated, tends to be most sensitive to changes in the network level of service. As a result, the four-step procedure may grossly over-estimate mode shift when in fact travel mode may be the last thing travelers wish to change in response to TDM measures.

Also stems from these three limitations is the problem that the four-step procedure will not be able to capture the full impact of a change in the travel environment. Suppose a drive-alone commuter routinely stops by at a grocery store on the way home from work. Faced with congestion pricing, this commuter may choose to take a bus to work, and go shopping by auto at a grocery store near the home base after returning home by bus. The trip-based four-step procedure is not capable of addressing such repercussions brought about by the commute mode change.

These examples illustrate that the four-step procedure is hardly applicable to the analysis of TDM measures. It is also insensitive to the effects of mounting traffic congestion or travel time savings due to traffic improvement. While some of the problems discussed in this section may be resolved by introducing new model elements or modifying some of the components of the four-step procedure, the problems stemming from the atemporal, trip-based structure are difficult to eliminate. Consequently developing effective tools for TDM analysis is impractical within the framework of the four-step procedure.

3. WHY THE ACTIVITY-BASED APPROACH?

The activity-based approach provides a coherent framework for travel behavior analysis and demand forecasting. While statistical associations, rather than behavioral relationships, drove model development of the components of the four-step procedure, the activity-based approach starts with the recognition that a rigorous understanding of travel demand will follow from an understanding of why and how activities are engaged over a span of time. Another important distinction is the recognition that trips cannot be analyzed one by one independently because the activities engaged over a period of time are linked to each other, and consequently the trips made to pursue these activities are also inter-related.

Because the activity-based analysis attempts to develop model systems based on a rigorous understanding of why people travel, resulting models are applicable to a much wider range of situations than is the trip-based four-step procedure. As the examples presented later in this paper show, the activity-based approach offers a better framework for the analysis of TDM measures. The issue of induced or suppressed trips can also be entertained with the approach. In fact most, if not all, of the problems of the four-step procedure described in the previous section can be resolved by adopting the activity-based approach.

[3] Keith Lawton brought this possibility to the author's attention.

There are several factors that have made activity-based models practical tools for travel demand forecasting (Kitamura *et. al.*, 1995a). They are: accumulation of activity-based research results; advances in survey methods (e.g., stated-preference (SP) and time-use survey methodologies) and statistical estimation methods; and advances in computational capabilities and supporting software (database software, GIS, etc.). These factors together have created an environment where models of travel behavior can be developed while adhering to the principles of the activity-based approach. In particular, activity-based micro-simulation of travel behavior has become a practical tool for transportation planning and policy analysis.

The advantages of the activity-based approach are summarized in Kitamura *et. al.* (1995a) as:

- *daily behavior*: treats a daily activity-travel pattern as a whole, thus avoids the shortcomings of the conventional trip-based methods;
- *realism*: incorporates various constraints governing trip making, facilitating realistic prediction and scenario analyses; and
- *induced demand*: by representing activity engagement behavior, the activity-based approach can rigorously address the issue of induced or suppressed demand.

In addition, activity-based micro-simulation of activity engagement and travel offers the following advantages:

- *time of day*: predicts travel behavior along a continuous time axis;
- *TDM evaluation*: is capable of realistically assessing the impact of TDM measures on the entire daily travel demand;
- *flexible* and *versatile*: can be modified for specific study objectives or to address various policy scenarios, e.g., to evaluate effects of day-care facilities at work, extended transit service hours, or new transit service;
- *accuracy control*: using synthetic household samples,[4] can produce results with desired levels of spatial and temporal resolutions; and
- *comprehensive evaluation tool*: activity-based approach simulates the entire daily activities and travel. Therefore the effect of a transportation policy on the entire daily activity, not just commute trips, can be evaluated, leading to better benefit measures.

The activity-based approach implies an expansion of the analytical scope because its subject is not limited to the trip. This naturally leads to increased levels of data requirements and analytical complexities. The advantages offered by the approach, in particular the ability to overcome the limitations of the conventional trip-based methods and to address policy options that are important in current planning contexts, more than outweigh the disadvantages. In fact practical forecasting models are being developed as reported later in this paper.

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[4] See Beckman *et. al.* (1995) and Kitamura (1996).

4. WHAT ACTIVITY-BASED TRAVEL DEMAND FORECASTING MUST SATISFY

When the reduction of peak-period congestion was the major concern of urban transportation planning, daily travel volume by network link was considered as a sufficient measure for planning exercises. The requirement that transportation planning analysis must incorporate emissions analysis, has drastically changed the prerequisites for travel demand forecasting models. In this section, new requirements for travel demand forecasting models in general are reviewed briefly. Following this, requirements for activity-based models are discussed.

Weiner (1993) lists as emissions modeling requirements the six items shown in Table 1. What is evident from the table is that methodologies are called for by which:

- trip starting time and ending time can be determined in a logically coherent manner;
- elapsed time between successive two trips by the same vehicle can be estimated such that whether the latter trip involves a cold start can be determined;
- vehicle type is explicitly treated; and
- day-to-day variations and seasonal variations in travel demand are appropriately captured.

It would be clear that the most coherent and robust approach to address the first two issues would be to incorporate the time-of-day dimension into the model framework. This is being achieved in some micro-simulation models systems as reviewed later in this paper.

Although several models of household vehicle type choice and utilization have been developed in the past (see Kitamura, 1992), none has been adopted by MPOs so far. More critically, these vehicle type choice and utilization models forecast the total *annual* VMT for each household vehicle, but do not match vehicles and trips. In other words, these models do not determine how the vehicles in a household fleet are assigned to the trips made by the respective household members. Consequently, the information available from them does not support the emissions analysis with the spatial dimension. The most coherent and robust approach to address this issue would be to explicitly model the process of vehicle allocation to trips. This is an area where little attention has been directed in the past.

Table 1
Emissions Modeling Requirements as
Identified in Weiner (1993)

• VMT by hour of the day by grid square
• Average speeds by hour by grid location
• Vehicle mix by hour of the day by grid square
• Proportion of cold starts by hour of the day
• Seasonal variation in VMT, vehicle mix, etc.
• Annual growth in VMT

There is an increasing recognition that predicting travel demand for a “typical” weekday does not adequately support transportation planning decision making. When traffic congestion is not limited to the traditional peak periods of commute traffic, ignoring weekend days can no longer be logically supported. Furthermore, by concentrating “average” travel demand, the “typical” weekday approach offers no information on the distribution of travel demand over a year. Consequently the approach is incapable of supporting the prediction of the frequency of air quality standard violations. Much work is needed in this area, in terms of both data collection and model development.

Activity-based models, especially the micro-simulation approach described later, meet many of these requirements imposed on travel demand models by the current planning needs. In addition to these requirements, there are several “desirable” features of activity-based forecasting models. Useful models of travel demand analysis and forecasting have been developed that do not necessarily possess all of these desirable features. Yet, developing logically coherent and robust models of activity and travel that are applicable to a wide range of policy analyses, calls for additional requirements. The following list is prepared with short-term forecasting in mind:

- *Mechanisms of activity engagement*: It is desirable that a model of activity-travel behavior explicitly represent the mechanism of activity engagement, while considering the needs and desires for activities and taking into account the availability of resources (e.g., time and vehicles). In addition, it is critically important for travel demand forecasting that the decision to change activity location be explicitly modeled (e.g., a series of comparison shopping activities may be pursued at several different locations, generating a number of trips).

- *Internal consistency*: The model should faithfully represent spatial and temporal continuity of movement, time-space constraints (e.g., Hägerstrand’s prisms), continuity in travel mode and various coupling and institutional constraints (Hägerstrand, 1970).

- *Comprehensive activity itinerary*: All activities, both in-home and out-of-home, should be included within the scope of the model, and the substitution between in-home and out-of-home activities should be considered.

- *Activity scheduling*: Forming an itinerary for a day (or a longer span of time) involves placing the activities to be engaged in a sequence (*sequencing* activities) and planning the starting time for each activity (*timing* activities). Previous studies (e.g., Kitamura, 1984) have revealed tendencies in activity sequencing that more mandatory activities tend to be pursued first. It is also expected that preferences do exist with respect to the timing of activities. Tendencies and preferences about activity sequencing and timing must be represented in a model of activity-travel behavior.

- *Inter-personal linkages*: The household is a unit where tasks are assigned to, resources are allocated to, and activities are engaged jointly by its members. Task assignment, resource allocation and joint activity engagement should be properly represented since travel demand generated by a household is determined by these inter-personal interactions.

- *Temporal variations*: It is required that variations in travel demand from day-to-day,[5] between weekdays and weekend, and across seasons be represented. For the purposes of emissions analysis, it is desired that the annual distribution of link traffic volumes be estimated.

- *Trip Attributes*: Travel demand must be forecast in terms of link travel volume by mode by time of day. As indicated in Table 1, emissions analysis using currently available emissions models requires that vehicle-miles traveled, average speed, fractions of hot and cold starts, and vehicle mix be forecast by small geographical area (grid). If these macroscopic indicators of travel demand are to be forecast by aggregating the attributes of individual trips, then vehicle type and hot/cold start must be determined as trip attributes in addition to the traditional measures of origin, destination, starting time, ending time, and mode.

Additional requirements exist for long-term forecasting models, including the representation of: changes in demographic and socio-economic characteristics of the region (including household members' employment status and household vehicle holdings) and the interaction between transportation and land use (including households' residential location choice).

Data collected by conventional methods and maintained by MPOs support some of the model development efforts that are called for by these requirements. It is, however, needed that data requirements be identified and data collection methods be refined toward the development of fully activity-based demand forecasting models.

5. STRUCTURAL-EQUATIONS APPROACHES TO ACTIVITY-BASED DEMAND FORECASTING

Structural equations modeling approaches have been used to capture relationships among macroscopic indicators of activity and travel, and to explore how these indicators are associated with variables that are considered to "explain" behavior, e.g., household structure and vehicle ownership. Structural equations approaches facilitate the examination of alternative hypotheses about the "causal" relationships among behavioral indicators, while reducing computational requirements substantially, even when limited-dependent variables are involved, by adopting the method of moments for the estimation of model coefficients (see Bollen, 1989). Examples can be found in RDC, Inc. (1993), Golob and McNally (1995) , Golob *et. al.* (1996), and Kitamura and Fujii (1996).

Golob *et. al.* (1996) presents probably the most elaborate model system in this group of studies. The endogenous variables of the model system are: "work/school activity duration," "work/school journey time," "maintenance activity duration," "maintenance journey time," "discretionary activity duration," and "discretionary journey time." Maintenance activities include "weekly grocery shopping, pick up and drop off passengers, personal business and 'other' activities," and discretionary activities include "other types of shopping, eating out, and visit/social/sport." Sex, income, presence of children, marital status,

[5] See Pas (1988).

occupation and home ownership are used as exogenous variables. In addition, the following set of mode use indicators is developed and used as exogenous, segmentation variables in the model: "exclusively car," "car + walking or bicycling only," "car + public transport," and "exclusively mode(s) other than car." Model coefficients are estimated by segment while constraining selected coefficients to be common among subsets (or the entire set) of the segments. This is equivalent as incorporating interaction terms that consist of combinations of an exogenous variable and one of the segmentation variables. Based on the results of model estimation, observations are made as to how the exogenous variables are differently associated with the endogenous variables across the mode use groups. Golob and McNally (1996) have further extended the analytical scope by including inter-personal interactions.

These structural equations models have offered insights into the relationship among activity engagement (often expressed in terms of time allocation) and travel. These model systems, however, offer no explicit treatment of the decision mechanisms underlying activity engagement. They represent a translation of a set of hypotheses into a system of simultaneous equations that involve "causal" links, such as "income affects expenditure," that are expressed as linear equations of (latent) endogenous and exogenous variables. This limits the richness of the behavioral theories that can be incorporated into the model system; relationships derived from theoretical considerations must be simplified to the form, "A affects B." In addition, no structural equations models have been developed where constraints on behavior (e.g., the total time available is limited to 24 hours per day) are explicitly introduced. Consequently care must be exercised when applying these models in cases where extrapolation beyond the relationships embedded in the estimation data set, is involved. Another limitation is that structural equations models can represent multinomial choices only approximately. In terms of travel demand forecasting, the models developed so far adopt aggregate representation of travel demand (e.g., total number of trips, travel time expenditure by trip purpose, or total VMT), and therefore do not support the analysis of travel demand where the spatial and temporal dimensions become critical, such as traffic congestion, pollutant emissions, and evaluation of congestion pricing.

Structural equations models nevertheless constitute a powerful approach to the analysis of travel demand. In particular, it facilitate expeditious exploration of alternative behavioral hypotheses and development of quantitative model systems of activity and travel that are capable of offering results that cannot be produced with the conventional model system. This can be seen in the two application examples presented below.[6]

5.1 Example I: Evaluation of Induced Trips

[6] The discussions in the rest of Section 5 draw from Kitamura, Pas and Fujii (1996).

The first example is based on a structural equations model system of commuters' time use and travel after work.[7] The data used in the study were collected in 1994 as part of an evaluation study of the impact of new Wangan (Bayshore) Line of the Hanshin Expressway system in the Osaka-Kobe metropolitan area. The survey adopted self-administered mail-out, mail-back questionnaires, which were distributed to 4,714 households along the Wangan Line and several competing routes. Usable responses were obtained from 1,257 individuals of at least 16 years old, in 594 households (response rate of 12.6%). A one-day activity diary was included in the survey instruments. The diary collected, for each activity, information on: the activity type, beginning time, ending time, facility type, type of accompanying person(s), spatial fixity, and temporal fixity. For each trip, information was collected on: travel mode, departure time, arrival time and number of accompanying persons.

The structural equation model system of mobility and time use included as its endogenous variables:

- number of trips after work and before returning home for the first time,
- total out-of-home activity duration (excluding travel) after work and before returning home for the first time,
- increase in travel time due to trips made to engage in out-of-home activities after work and before returning home for the first time,
- frequency of home-based trip chains after returning home for the first time till retiring for the day, and
- total time spent at home after returning home for the first time till retiring for the day.

The exogenous variables include: commute duration, regular work starting time, regular work ending time, flexible work hours, number of hours overworked, age, work trip mode, number of restaurants in work zone, preference indicator for out-of-home activities, and preference indicator for in-home activities.

The estimated model system was used to estimate the impacts of a 10-min. reduction in commute time on time use and travel. The results are summarized in Table 2. The model system indicates that the 10-min. travel time saving will lead to an increase in the average total out-of-home activity duration by 1.88 min. and an increase in the total time spent in home by 7.11 min. The average total travel time increases by 0.36 min. Over 70% of the time saved is applied to additional in-home activities, and about 19% to out-of-home activities. The results here indicate that a relatively small number of trips are induced by travel time savings of the magnitude analyzed here, and that much of the travel time saved is spent at home.

Table 2

Effects of Commute Time Reduction on Time Use and Travel

	Base Case	10-min. Reduction	Difference

[7] For time use analysis in transportation planning in general, see Pas and Harvey (1991). Examples of empirical studies can be found in Kitamura *et. al.* (1992, 1995b).

Total out-of-home activity duration	25.56	27.44	+1.88
Increase in travel time	6.78	7.14	+0.36
Frequency of home-based trip chains	0.03	0.04	+0.01
Total time spent at home	216.1	223.2	+7.11

5.2 Example II: Time Use Utility

In another modeling effort an attempt is made to formulate the utility of daily activities. The utility of an activity is assumed to be the function of the time allocated to it and the attributes of the individual. The coefficients of the utility function are specified as linear functions of subjective preference ratings given by the respondent for respective types of activity.

The resulting model system is applied in this example to evaluate alternative improvement strategies by estimating how travel time reductions they produce may affect the daily utility. Consider a simple network which encompasses the home base, the work base and an activity center. In the base case, the travel time between home and work is 1 hr., that between work and the activity center is 30 min., and that between the activity center and home is 1 hr. Consider the following two improvement strategies:

Strategy 1: reduce the travel time between work and activity center by 15 min.
Strategy 2: reduce the travel time between work and home by 7.5 min., one way

Suppose work ends at 6:00 PM, and the commuter may choose to make a stop for discretionary activity on the way home at the activity center. The impacts of the two strategies on the activity and travel of a hypothetical person are estimated for the activity and travel of the commuter after work, and are summarized in Table 3 for the case where no stop is made and the case where a stop is made. Along with the amount of time allocated to out-of-home discretionary activities, travel time, and in-home activity time, the table shows the probability that an out-of-home discretionary activity will be pursued on the way home, and the expected utility associated with the activity pattern.

Table 3

Effects of Travel Time Reduction on Activity Engagement and Time-Use Utility

	Base Case		Strategy 1		Strategy 2	
	No Stop	Stop	No Stop	Stop	No Stop	Stop
Discretionary out-of-home time (hr.)	0.000	0.902	0.000	0.975	0.000	0.902
Travel time (hr.)	1.000	1.500	1.000	1.250	0.875	1.500
In-home time (hr.)	5.000	3.597	5.000	3.775	5.125	3.597
Time returned home	19:00	20:24	19:00	20:14	18:53	20:24
Probability of choice	0.538	0.462	0.497	0.503	0.562	0.438
Expected time use utility	0.290	0.138	0.290	0.303	0.389	0.138

In the case a stop is made on the way home, the 15-min. travel time reduction between work and activity center under Strategy 1 results in an increase in out-of-home activity time by 0.073 hr. (4.3 min.), which is about 30% of the travel time saving. The remaining 10.7 min. is assigned to in-home activities. The utility associated with the pattern with a stop increases from 0.138 to 0.303, with the choice probability increasing from 0.462 to 0.503. Likewise, it can be seen that the utility of the pattern without a stop increases from 0.290 to 0.389 under Strategy 2 where the travel time between work and home is reduced by 7.5 min. The conventional unconditional expected representative utility (denoted as "E[V]") and the expected representative utility of a pattern given that the pattern is chosen ("$\ln\Sigma e^V$"), are shown below for these three cases:[8]

	E[V]	$\ln\Sigma e^V$
Base case	0.220	0.910
Strategy 1 (improvement between work and activity center)	0.297	0.990
Strategy 2 (improvement between work and home)	0.279	0.964

It can be seen that Strategy 1, which involves the improvement of travel time between work and activity center, produces a larger expected utility than Strategy 2. Consistent with this, the representative utility of a chosen pattern reveals that Strategy 1 in fact would offer more benefit.

The analysis of this example is limited in the sense that only two simple alternative activity-travel patterns are considered for just one person. The results have nonetheless shown that the model system can be used to evaluate transportation planning options while considering changes in utilities associated with activity-travel patterns.

6. MICRO-SIMULATION APPROACH TO ACTIVITY-BASED DEMAND FORECASTING

The second approach is the micro-simulation of activity engagement and trip making. Several model systems that have been developed attempt to represent the cognitive processes that accompany activity scheduling and trip planning. These developments reflect advances made in models of human cognition, decision making and problem solving. For reviews of developments in activity scheduling, see Axhausen and Gärling (1992) and Gärling *et. al.* (1994).

[8] The discussion here is based on the assumption of the logit model of discrete choice that the perceived utility of an alternative, say j, can be expressed as $U_j = V_j + e_j$, where V_j is the "representative utility" and e_j is an error term with an extreme-value distribution. Because the utility measures that can be identified from the analysis here are relative measures, E[V] and $\ln\Sigma e^V$ are not comparable to each other.

Preceding the current efforts to develop models of activity scheduling is CARLA (Jones *et. al.*, 1983), which is a model system that identifies feasible alternative schedules from all possible schedules by applying systems of constraints. STARCHILD (Root & Recker, 1983; Recker *et. al.*, 1986a, b) is a model system where activity-travel behavior is conceptualized as the choice of a particular schedule from all possible schedules based on utility measures. Following these predecessors are *computational process models* that describe how people formulate and execute schedules. As the name indicates, the computational process approach focuses on the process of decision making and captures heuristics and short-cuts that are involved, as opposed to assuming overriding behavioral paradigms such as utility maximization. One example of computational process models is the *production model* (Newell & Simon, 1972), which is a model of human problem solving comprising a set of rules, or condition-action pairs that specify an action to be executed when a condition is encountered. Several computational process models of activity scheduling have so far been developed, including: SCHEDULER (Gärling *et. al.*, 1989, 1994), SMASH (Ettema *et. al.*, 1993, 1994), DynaMIT (Tasker and Axhausen, 1994), and the framework presented in Vause (1995). These model systems are reviewed in detail in Kurani and Kitamura (1996). The discussions in the rest of this section are concerned with AMOS (Kitamura *et. al.*, 1993, 1995a, 1996; Pendyala *et. al.*, 1995), and PCATS (Kitamura, Fujii & Otsuka, 1996; Kitamura and Fujii, 1996), which have been applied to produce forecasts.[9]

6.1 PCATS

PCATS simulates the individual's activity engagement and travel within Hägerstrand's prisms. In defining prisms for each individual, it is assumed that the simulation period, say a day, can be divided into periods of two type: *open periods* and *blocked periods*. Open periods are ones in which the individual has the option of traveling and engaging in activities. Blocked periods, on the other hand, are ones where the individual has committed to engage in certain activities at certain locations. Activities participated within a blocked period shall be called *fixed activities*; those pursued in an open period shall be called *flexible activities*.[10] Given the speed of travel, the ending time and location of a blocked period and the beginning time and location of the subsequent blocked period, define a time-space prism in which the individual's activity and travel are contained. It is assumed that the individual makes activity engagement and travel decisions at the beginning of each open period and also when an activity is completed within a open period. It is thus assumed that activity engagement decision is made sequentially, conditioned upon past activity engagement.

[9] The discussions in the rest of Section 6 are excerpts from Kitamura and Fujii (1996).

[10] The activity categories used in PCATS are: sleep, personal care (other than taking bath), personal care (bath), child care, meal, domestic chore, work and work-related, school and study, social, grocery shopping, comparison shopping, hobbies and entertainment, sports and exercises, TV viewing, reading, resting, medical and dental, and others. A set of assumptions are adopted to determine whether an activity is fixed or flexible. Sleep is always classified as a fixed activity. Personal care (other than taking bath), personal care (bath), TV viewing, reading, and resting, on the other hand, are always classified as flexible. Activities of the remaining types are classified as fixed if the respondent indicated in the survey that the activity was subject to both temporal and spatial constraints; otherwise they are regarded to be flexible.

6.1.1 Outline of PCATS

PCATS is based on a sequential decomposition of the probability associated with an activity-travel pattern, namely,

$$\Pr[A, B, C, ...] = \Pr[A]\Pr[B|A]\Pr[C|A, B] ....$$

where A, B, C, ... refer to events brought about by activity-travel decisions, e.g., leave for work at 6:30 A.M. by car. Using this sequential decomposition rule, the multiple decisions underlying an activity-travel pattern can be expressed by a product of probablistic elements, each associated with an activity episode or trip. Furthermore, each of these probablistic element can be further decomposed into conditional probabilities associated with respective aspects of activity-travel decision, e.g., activity type, activity duration, location, and travel mode (if relevant). Now, there are alternative sequences of decomposition that are equivalent, e.g.,

$$\Pr[A, B, C] = \Pr[A]\Pr[B|A]\Pr[C|A, B] = \Pr[B]\Pr[C|B]\Pr[A|B, C] = ...$$

Then a particular sequence may be preferred and selected considering: theoretical support, policy sensitivity, and ease of modeling. The sequence adopted in the development of PCATS can be depicted as: activity type $\rightarrow$ location $\rightarrow$ travel mode $\rightarrow$ activity duration.

Activity Duration Models are first discussed because they are used in the activity type choice model presented next.[11] The distribution of durations of flexible activities is determined by activity type, assuming that the parameters of the distribution (the mean and a shape parameter) is a function of personal attributes and other explanatory variables. Weibull distributions are exclusively used in the current version of PCATS.[12] The explanatory variables used in the duration models are: person and household attributes, past activity engagement, time of day, time availability and location type indicator. The location types used here are {home, non-home}. For detailed descriptions of model estimation results, see can be found in Otsuka (1996).

The Activity Type Choice Model developed here has a two-tier structure, and is formulated as a nested-logit model. In the first (upper) tier, one of the following three broad classes of activities is chosen: in-home activity, activity at (or near) the location of the next fixed activity, and general out-of-home activity. Exactly which alternatives can be included in the choice set is determined considering prism constraints. In other words, the formation of choice sets in PCATS simulation is governed in part

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[11] For earlier studies on the subject, see Mannering (1993), Niemeier and Morita (1996), Bhat (1996a, 1996b), Ettema *et. al.* (1995) and Kitamura, van der Hoorn & van Wijk (1995).

[12] This is not to exclude the possibility that in the future more suitable distribution functions may be identified and used in PCATS.

by prism constraints. The second tier under "in-home activity" includes: engage in out-of-home activity subsequently, and do not engage in out-of-home activity within the current open period. If the former is the case, then the duration of the in-home activity will be determined, and the activity choice model will be applied again with the "in-home activity" alternative excluded from the choice set. If the latter is the case, then the travel to the location of the next fixed activity will be simulated. Likewise, if the option of "activity at (or near) the location of the next fixed activity" is selected in the first tier, then the travel to the next fixed location will be simulated.

If "general out-of-home activity" is chosen, then the activity type is selected in the second tier. Activities are classified into the following six activity types, which comprise the choice set in the second tier: meal, social, grocery shopping, comparison shopping, hobbies and entertainment, and sports and exercises. The explanatory variables used to model the choice of out-of-home activity type include: personal attributes: age, sex, home-maker or not, time of day, and probability that the activity duration fits within the open period.

The Destination and Mode Choice Model is formulated also as a nested-logit model. The first tier concerns the choice of destination, and the second tier the conditional choice of travel mode, given the destination. In the current version of PCATS, one model is applied to all trips; this is restrictive and in the future models will be differentiated by trip purpose. Municipalities are used as the unit of geographical aggregation in this study. Travel modes are classified as {public transit, automobile, bicycle, walk}. The explanatory variables used to account for destination choice are: zonal population, the number of commercial establishments, intra-zone destination dummy, the possible minimum travel time to the destination zone then to the location of the next fixed activity, and the probability that the provisional activity duration fits within the open period given the activity is pursued at the destination zone. The explanatory variables for conditional mode choice, given a destination are: age, sex, employment status, driver's license holding, household income, number of vehicles available, time of day, travel time and cost by mode, and number of transfers, intra-zone trip dummy, and location type indicator (indicators of the combination of the current location type and the location of the next fixed activity).
This model is used in PCATS to generate a destination and mode for each trip. As is the case for activity choice, only those destination-mode pairs that are feasible in light of prism constraints and coupling constraints (primarily for auto availability), are included in the choice set.

The duration of the activity is finally determined, given its type, location, and the mode used to reach the activity location. The activity duration models described earlier are used here while considering prism constraints. The maximum possible activity duration is first determined based on the size of the prism, which is a function of the speed of travel, the location of the trip origin, the location of the activity, and the location of the next fixed activity. Then the distribution as given by the duration model for the activity type is truncated at the maximum, i.e., a probability mass equaling to the probability that the activity duration will exceed that maximum is placed at the maximum. The resulting mix distribution is used to generate activity durations in the simulation.

6.1.2 Validation

A validation analysis is conducted to determine how well the simulation system replicates observed activity and travel patterns. In the analysis, expected values obtained from the simulation are compared against observed values for several indicators of activity-travel patterns. Expected values are obtained by averaging the results of 100 simulation runs performed for each sample individual. The results of the validation study are summarized in Table 4 for 374 sample individuals whose activity records are complete.

Table 4
Results of the Validation Study

	Predicted		Observed			
	Mean	S.D.	Mean	S.D.	t	R^2
Total travel time	116.3	70.7	127.9	87.1	-2.00	0.622
In-home flexible activity duration	314.5	152.9	288.7	191.0	2.04	0.673
Out-of-home flexible activity duration	28.4	72.3	39.6	75.6	-2.07	0.329
Number of non-work destinations	0.071	0.61	0.31	0.58	-5.42	0.169
Number of non-work trip chains	0.059	0.28	0.013	0.11	2.86	-0.027
Number of trips	2.89	1.56	3.38	1.79	-4.00	0.576

S.D.: standard deviation across sample individuals
t: t-statistics associated with the difference between the predicted and observed values (not based on the standard deviations associated with "predicted" values)
R^2: Pearson correlation coefficient between predicted and observed values

It can be seen from Table 4 that total travel time, in-home flexible activity duration, and number of trips are relatively well represented by the simulation. According to the t-statistics, however, predicted values and observed values are significantly different for all indicators (at a = 0.05). In particular, number of non-work destinations and number of non-work trip chains have very small correlation coefficients. The results point to possible deficiencies in the model components, especially the activity type choice models. The results, nevertheless, demonstrate that the simulation system can replicate the observation reasonably well, at least with respect to total travel time, in-home flexible activity duration, and number of trips.

6.1.3 Scenario Analysis

PCATS is now applied to assess how changes in the travel environment affect an individual's activity and travel. In this analysis a sample individual is selected and his activity and travel after work is simulated for each of the scenarios shown in Table 5.

Table 5

Scenarios Used in the Simulation Analysis

Scenario	Description
Base case	Work ends at 5:00 PM. A car is used to commute.
Scenario 1	Work ends at 6:00 PM. A car is used to commute.
Scenario 2	Work ends at 5:00 PM. Public transit is used to commute.
Scenario 3	Work ends at 5:00 PM. Car commute takes extra 30 min.

The sample individual's profiles are as follows:

> An employed male of 54 years old;
> household income in the 1,500,000 to 2,000,000 yen range
> has held a driver's license for 30 years;
> one vehicle available to the household;
> commutes to CBD Osaka;
> lives approximately 30 km to the south from Osaka along the Osaka Bay; and
> has good freeway access to the Osaka CBD.

The individual is assumed to be at the work location when work ends (which is assumed to be the ending point of a blocked period), and the next blocked period is assumed to begin at midnight. It is thus assumed that the entire evening period, after work till midnight, is an uncommitted block of time. Table 6 summarizes the results obtained by performing 100 simulation runs.

The frequency of the simple W-H pattern increases from 84 in the base case to 91, 89 and 90, respectively, in the three scenarios. Quite notable in Scenario 1, where work ending time is moved to 6:00 PM, is the substantial reduction in the out-of-home activity duration and the slight reduction in the travel time associated with the W-O-H pattern. The in-home activity time does not show very much change. The shortening of the after-work open period caused by the change in work ending time has prompted the individual to engage in out-of-home activities less frequently. When the W-O-H pattern is engaged, the activity location is closer and the activity duration is much shorter, presumably to accommodate the tighter time constraints. These tendencies are not found for the W-H-O-H pattern, however. Yet, it is cautioned that the frequency of out-of-home activity engagement is small in the simulation results and the statistics presented under the W-O-H and W-H-O-H patterns contain large variations.

Similar reductions in out-of-home activity engagement can be found for Scenarios 2 and 3. The mean travel times associated with pattern W-O-H exhibit increases of less than 15 min. from the base case, while the activity times decrease by 15 to 20 min. Much larger changes are associated with the W-H-O-H pattern. This, however, is at least in part due to the small sample size.

This scenario analysis has demonstrated that PCATS facilitates the analysis of time-oriented policies such as changes in work schedules while explicitly considering time-space constraints in the analysis. PCATS also represents the repercussions of a change in the travel environment, including induced (or suppressed) travel and changes in activity location and duration.

Table 6

Results of Scenario Simulation with a Sample Individual

		After-work Travel Pattern[1]			
		W-H[3]	W-O-H	W-H-O-H	Other
Base case	Frequency	84	8	7	1
	Travel time[2]	51	122	160	
	In-home time[2]	369	188	208	
	Out-of-home time[2]	0	109	52	
Scenario 1	Frequency	91	5	4	0
	Travel time	51	114	184	
	In-home time	309	177	115	
	Out-of-home time	0	69	62	
Scenario 2	Frequency	89	6	5	0
	Travel time	79	135	180	
	In-home time	341	190	155	
	Out-of-home time	0	94	85	
Scenario 3	Frequency	96	6	2	2
	Travel time	81	136	214	
	In-home time	339	195	178	
	Out-of-home time	0	89	29	

[1] W-H: work → home. W-O-H: work → other → home. W-H-O-H: work → home → other → home

[2] In minutes. Out-of-home time excludes travel time.

[3] Since static travel time is used in the simulation, there is no random element in travel time (and therefore in in-home time) for the first travel pattern, "W-H," where the individual returns home immediately after work and engages in no out-of-home activity.

Yet, PCATS is still in its early stage of development; it would be more appropriate to say the model system as presented in this study is an initial prototype. For example, the destination-mode choice model is not differentiated by trip purpose as noted earlier. The model system does not yet have the capability to endogenously generate fixed activities. There are many areas where development, extension and refinement are needed. Nevertheless it can be concluded that the study has demonstrated that activity-travel behavior in time-space prisms can be simulated reasonably well and that travelers' responses to changes in travel time or work schedules can be examined using the micro-simulation model system. The PCATS model system is readily applicable to other types of scenarios, such as changes in store hours or extended operating hours of public transit, which are difficult to address with the conventional trip-based models that do not incorporate the time dimension and disregard time-space constraints. An additional future task is to incorporate into PCATS the behavioral mechanism for activity engagement. The "utility-maximizing," nested-logit model of activity type choice incorporated in

PCATS captures the salient tendencies associated with activity type choice; it, however, hardly captures the reason for activity engagement. Effort is ongoing toward the development of a model of activity engagement which represents the motivations for activity engagement and which will make PCATS truly behavioral.

6.2 AMOS

Activity-Mobility Simulator (AMOS) is a micro-simulation model system of individuals' adaptation behavior which predicts changes in travel behavior that will follow a change in the travel environment. The individual's adaptation behavior is characterized as a trial-and-error experimentation process. The development of AMOS has been motivated by the recognition that the traditional, trip-based, four-step procedures are incapable of incorporating TDM and other policy measures that are now the primary focus of urban transportation planning.

A prototype of AMOS has been developed and implemented in the Washington, D.C., metropolitan for the evaluation of selected TDM measures. AMOS is currently being implemented in three major metropolitan areas of California. In this implementation, AMOS is being combined with: a household vehicle transactions model which predicts the timing and type (addition, replacement, or disposal) of vehicle transactions and the types of acquired vehicles; and a demographic simulator which predicts the evolution of demographic and socio-economic attributes of households. AMOS will thus serve as a long-term forecasting model. Detailed discussions of AMOS can be found in RDC (1995), Kitamura *et. al.* (1993, 1995a) and Pendyala *et. al.* (1995). The description of the AMOS components below draws from Kitamura *et. al.* (1995a).

6.2.1 AMOS Components

AMOS comprises five main components and a reporting routine. In a nutshell, it functions as follows. First, how an individual may respond to a change in the travel environment caused by, say, a TDM measure, is determined by Monte Carlo simulation with a neural network that has been calibrated using results of a stated-response survey designed and administered for AMOS calibration. The individual's "base-line" travel pattern is then modified based on the response, and all necessary secondary and tertiary changes are made while considering a rule-base that represents a series of constraints and tendencies, including Hägerstrand's coupling constraints. Then the resulting modified pattern is evaluated against those patterns that have so far been generated, and is accepted when a set of rules is met. AMOS thus replicates an individual's trial-and-error search behavior for a better travel pattern based on the paradigm of satisficing. The structure and functioning of the model system is illustrated below by briefly describing each model component.

Baseline Activity-Travel Pattern Analyzer inspects "base-line" travel diary data and determines whether the diary data under consideration are complete, with all trips and pertinent information intact. It also checks whether the sample individual and/or her travel pattern falls in the categories targeted for analysis. Another major function it performs is to develop indicators of travel pattern characteristics (e.g., there is a stop during the commute trip) that feed into the Response Option Generator described next.

Response Option Generator is a key stochastic element of AMOS that produces response patterns to a change in the travel environment. The input to the Generator consists of: household and person attributes, network and land use characteristics, characteristics of the change in the travel environment (e.g., TDM attributes), and the indicators of the baseline activity-travel pattern characteristics prepared by the Analyzer. Given these, the Generator simulates how the sample individual response to the TDM measure.

The central component of the Generator is a neural network. Its use draws from a branch of cognitive science called “connectionism,” in which it is postulated that humans process information by breaking it down into smaller elements that are inter-connected with different levels of intensity. In other words, human thinking is a process of connecting one informational element (e.g., a concept) to another. This idea can be depicted by a neural network, which can be “trained” to best replicate observed connection patterns between input (in this case TDM attributes) and output (response options).

Activity-Travel Pattern Modifier examines the baseline pattern and, if the response option from the Generator necessitates it, performs: (i) activity re-sequencing (re-arrangement of the order in which out-of-home stops are made), (ii) activity re-linking (re-combining of out-of-home stops into trip chains), (iii) mode and destination assignment, and (iv) trip timing adjustment. Such adjustments are needed primarily when a travel mode change or a departure time change implied by the response option, makes the baseline pattern infeasible or impractical. The Modifier then examines the feasibility of the resulting modified activity-travel pattern using a rule base.

Evaluation Routine assigns a utility measure to the modified activity-travel pattern using time-use utility functions (see RDC, 1993; Kitamura *et. al.*, 1995b). The attractiveness of the pattern produced by the Modifier is measured in terms of the utility generated by allocating time to, and engaging in, the in-home and out-of-home activities contained in the pattern. The utility functions have been developed using the time-use data obtained from the time-use survey conducted as part of the implementation study. The ongoing effort includes the generalization of the utility functions to include non-time elements such as mode attributes, monetary expenses, and timing of activities. Using the time utility concept, AMOS evaluates TDM measures while considering their impacts on the entire daily activity, not just on the commute trips which these measures often target.

Acceptance Routine compares the activity-travel patterns so far generated, and determines whether the search should continue or one of the patterns so far generated should be adopted. The routine represents the assumption that, based on the outcomes so far, the individual forms a subjective distribution of utilities associated with alternative patterns; assesses the likelihood of obtaining a better activity-travel pattern; and terminates the search when the cost of search exceeds the expected gain of searching further. Experiments are being designed to validate this theoretical search termination model and to estimate the parameters.

The output of the AMOS micro-simulation is modified and accepted travel patterns that represent individuals' responses to TDM measures.

6.2.3 AMOS Survey

A prototype of AMOS has been developed and implemented in the Washington, DC, metropolitan area. The implementation effort adopts the Metropolitan Washington Council of Governments (MWCOG) traffic analysis zone (TAZ) system and zone-to-zone network travel time matrices by travel mode. Network skim data are available for: drive alone (SOV), ride-sharing (HOV), public transit with walk access, and public transit with auto access. Travel times by bicycle and walk are estimated by applying assumed speeds (6.5 mph and 2.5 mph, respectively) to the centroid-to-centroid distance. The implementation effort thus utilizes as much spatial and modal information as available from the MWCOG data base.[13]

A three-phase survey, involving computer-aided telephone interviews (CATI), was conducted in November and December of 1994 to generate a data set to calibrate AMOS components. The survey included a *time-use* section which collected data on both in-home and out-of-home activities as well as details of each trip made. Also in the survey was a set of customized stated-response (or "stated adaptation") questions which asked respondents how they would respond to each TDM measure. Adult commuters who commuted at least three days a week were the target of the survey. For further information, see RDC (1995) and Pendyala *et. al.* (1995).

In the survey, respondents were given a description of a TDM measure, then asked in an open-ended format, "What would you do?" if the measure had been in fact implemented. Commute travel time and other pertinent parameters were customized such that the hypothetical scenario would closely represent each respondent's commute situation. Follow-on questions were asked to probe into details of the stated behavioral adjustment (e.g., how to drop off a child at the day-care when public transit is used to commute). The TDM measures included in the survey are described in Table 7.
Results of the TDM stated-adaptation section were used to train the neural network in the Response Option Generator. The resulting network consists of 45 input nodes, 8 output nodes, and two hidden layers. The input nodes may be grouped as: personal and household attributes, work schedule characteristics, commute characteristics, trip chaining characteristics, mode characteristics, and TDM scenarios. The eight output nodes comprise: change departure time, use transit to work, ride-share to work, ride bicycle to work, walk to work, work at home, do nothing different, and other (long-term responses treated as doing nothing in short-term policy analysis).

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[13] Note that travel time data used are *static*; possible changes in network service levels due to TDM measures are *not* reflected in the simulation.

Table 7
TDM Measures Included in the AMOS Survey in
the Washington, DC, Metropolitan Area

TDM #1	**Parking Tax**. Incremental parking tax at work place at - $1 to $3 per day in suburbs* - $3 to $8 per day in D.C. and central areas
TDM #2	**Improved Bicycle/Pedestrian Facilities**. Well-marked and well-lighted bicycle paths and a secure place to park a bicycle wherever respondent went.
TDM #3	**“Synergy” Combination of TDM 1 and TDM 2**
TDM #4	**Parking Charge Combined with Employer-Supplied Commuter Voucher.** Employers provide employees with a commuter voucher while employees must pay for a parking surcharge. - $40 to $80 per month for both voucher and surcharge
TDM #5	**Congestion Pricing**. Area-wide implementation of congestion pricing, effective from 6:00 AM to 9:00 AM and from 4:00 PM to 7:00 PM. - $0.15 to $0.60 per mile - 10% to 30% travel time savings
TDM #6	**“Synergy” Combination of TDM 4 and TDM 5**

*Different parameter values are assigned to respondents randomly within the range shown.

6.2.4 Simulation Results

Using the AMOS prototype described above, the effectiveness of the following TDM measures are evaluated:

- TDM #1, parking pricing: parking surcharge of $8.00 per day,
- TDM #4, parking pricing with employer-paid voucher: parking charge of $80 per month and a commuter voucher of $60,
- TDM #5, congestion pricing: congestion charge of $0.50 per mile, travel time reduction by 30%, and
- TDM #6, a synergy combination of TDM #4 and TDM #5: parking charge of $80 per month, commuter voucher of $60, and congestion charge of $0.50 per mile.

A total of 20 simulation runs were performed for each TDM measure.

The results of the analysis are summarized for TDM #1 and TDM #5 in Tables 8 through 10. The reader is cautioned that the number of sample households from the MWCOG data base that were available to the study was unfortunately very small and the results presented here are subject to sampling errors.[14] It must also be noted that this exercise has been made for illustrative purposes and the size of

[14] In the future the spatial and temporal resolution of micro-simulation results can be refined by using more households, possibly synthetic households distributed over the study area.

the sample used here, and some of the simplifying assumptions existent in the prototype, warrant neither generalization of the results obtained nor general assessment of the relative effectiveness of the TDM scenarios examined here.

Table 8
Baseline Travel Characteristics

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	42.2%	64.0%	31.1%	36.6%
Non-Work	57.8%	36.0%	68.9%	63.4%
TRAVEL MODE				
Auto - Driver	54.0%	65.1%	54.7%	45.5%
Auto - Passenger	18.4%	10.5%	18.9%	23.6%
Other	27.6%	24.4%	26.4%	30.9%
TRIP DURATION (min.)				
Total	18.5	21.7	22.0	13.4
Auto-Driver	21.6	24.5	24.9	15.2
Auto-Passenger	17.0	16.4	21.4	14.2
Other	13.6	16.4	16.2	10.1
HOT STARTS (%)	37.7%	34.9%	35.9%	37.8%
PERCENT OF TRIPS	100%	27.3%	33.7%	39.0%
TRIPS PER PERSON	3.21			

Baseline: The distribution of trip purposes (work vs. non-work), travel mode (auto-driver, auto-passenger, other), mean trip duration by mode, percent of hot starts, and average number of trips per person are summarized in Table 8 for AM peak, PM peak and off-peak periods. Slightly over 60% of the trips are work trips (including trips from work to home), with higher fractions during the morning and afternoon peaks. Overall over three-quarters of the trips are made by auto. The large fraction of trips by "other" mode in the afternoon peak period represents walk trips made in this period by this sample of commuters.

Parking Pricing (TDM #1): Results of simulation runs with TDM #1, parking pricing with a surcharge of $8 a day, are summarized in Table 9 The most notable change is in modal split. The fraction of auto driver trips decreased from 54.0% in the baseline case to 47.5%, and auto passenger trips from 18.4% to 16.4%. The fraction of "other" modes increased by 7.8% during AM peak, 6.3% in the PM peak and 4.4% during off-peak periods, respectively.
The overall average trip duration (in min.) shows only small changes between the two cases. Importantly, however, the mean "other" trip duration increased from 13.6 min. to 18.4 min. This suggests that long-distance commuters tended to remain auto commuters while shorter distance travelers adopted other options. The distribution of trips across morning peak, afternoon peak and off-peak

shows only minor changes. The fraction of morning peak trips decreased slightly from 34.9% to 34.5%, while that of afternoon peak trips increased from 35.9% to 37.4%. The average number of trips per person increased slightly from 3.21 to 3.31. This reflects activity re-linking as a result of a commute mode change, which resulted in more trips.

Table 9

AMOS Simulation Results: Parking Pricing (TDM #1)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	43.2%	63.2%	35.5%	35.4%
Non-Work	56.8%	36.8%	64.5%	64.6%
TRAVEL MODE				
Auto - Driver	47.5%	57.5%	48.6%	40.8%
Auto - Passenger	16.4%	10.3%	18.7%	23.9%
Other	36.1%	32.2%	32.7%	35.3%
TRIP DURATION (min.)				
Total	19.4	21.6	22.8	13.4
Auto-Driver	21.2	23.6	24.8	15.3
Auto-Passenger	16.5	16.4	21.4	14.2
Other	18.4	19.7	20.7	10.5
HOT STARTS (%)	37.4%	34.5%	37.4%	39.2%
PERCENT OF TRIPS	100%	26.9%	33.0%	40.1%
TRIPS PER PERSON	3.31			

Congestion Pricing (TDM #5): The results with congestion pricing at a level of $0.50 per mile with 30% reduction in travel time are summarized in Table 10. The fraction of auto trips, 50.2%, is higher with this TDM than with parking pricing (47.5%), but is lower than the baseline result (54.0%). Notable is the result that the reduction from the baseline in driver trips in PM peak is much smaller than that in the morning peak. Other than mode shares, the results of this TDM are very similar to those of TDM #1.

The exercise here has demonstrated that AMOS is capable of producing travel forecasts by simulating individuals' daily travel patterns. It has also shown that the TDM measures examined in the study do have certain impacts on travel demand. From model development viewpoints, results are very encouraging as they indicate activity-based models can be implemented in a metropolitan region and can produce forecasts for policy analysis.

The results may seem less encouraging from transportation policy viewpoints, however, because the effects of the TDM scenarios examined here are small, and because there are only a few discernible differences among the impacts of the respective TDM scenarios. These results may be simply due to the small sample used in the exercise. It is conceivable that the commuters in the sample had very limited alternative commute options and were able to respond within very narrow ranges to whatever TDM scenarios being implemented. Whether this observation can be generalized or not needs to be determined in the future by the analysis of full data set.

Table 10

AMOS Simulation Results: Congestion Pricing (TDM #5)

	Total	AM Peak	PM Peak	Off-Peak
TRIP PURPOSE				
Work	43.0%	64.4%	35.6%	36.5%
Non-Work	57.0%	35.6%	64.4%	63.5%
TRAVEL MODE				
Auto - Driver	50.2%	56.3%	51.9%	39.7%
Auto - Passenger	17.0%	10.3%	18.3%	22.2%
Other	32.8%	33.4%	29.8%	38.1%
TRIP DURATION (min.)				
Total	19.0	23.0	22.6	13.5
Auto-Driver	21.4	23.5	24.5	16.1
Auto-Passenger	17.3	16.4	21.8	14.5
Other	16.2	24.2	19.9	10.2
HOT STARTS (%)	36.8%	34.5%	36.5%	34.9%
PERCENT OF TRIPS	100%	26.9%	32.2%	39.0%
TRIPS PER PERSON	3.30			

Another possibility is that the Response Option Generator has not been fine-tuned enough to be able to detect possibly minute differences in commuters' responses to different TDM measures. In particular, the results suggest that a neural network be developed for each TDM measure separately.[15] The invariance in simulation results across the TDM scenarios may also be due to the limitations of the prototype used for the analysis. For example, destination choice has not been implemented in the prototype. In addition, the simplistic evaluation and acceptance rules adopted in the prototype may have resulted in premature search termination for each commuter, possibly leading to the acceptance of the baseline patterns with a higher probability than it should receive.

This exercise nonetheless has demonstrated that a micro-simulation model system of daily travel behavior, which adheres to the principles of the activity-based approach, is not only feasible but also is capable of providing a practical tool for policy analysis. The implementation of the AMOS prototype in the Washington, D.C., metropolitan area utilizes the data base maintained by the MPO of the area. The

[15] In the prototype used in this study, the neural network is designed to be able to handle all TDM scenarios examined.

medium scale survey (about 650 respondents) used in this study can be modified to entertain a wide range of TDM measures, making AMOS a flexible and realistic tool for transportation policy analysis. As noted earlier, efforts are ongoing currently on several fronts to expand the scope of AMOS by incorporating: vehicle transaction and utilization behavior, vehicle allocation, synthetic generation of households and their activity-travel patterns. Planned research activities include the development and incorporation of models for: search termination, activity engagement, time allocation, inter-person interaction, and multi-day behavior.

7. CONCLUSION

This paper has offered an overview of the roles and advantages of the activity-based approach in travel demand forecasting, and discussed requirements for demand forecasting models in current transportation planning contexts. Application examples are presented with two classes of activity-based model systems: more macroscopic structural equations model systems, and micro-simulation model systems. These model systems are in their early stages of development and the examples presented are limited in their scopes. The results presented in this paper have, nevertheless, demonstrated that activity-based model systems are practical tools for policy analysis that overcome the weaknesses of conventional models. The results offer strong support for the development and implementation of full-scale model systems.

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REFERENCES

Axhausen, K.W. (1990) Judging the day: A synthesis of the literature on measuring the utility of activity patterns. Transport Studies Unit Working Paper 561, Oxford University, Oxford.

Axhausen, K.W. (1995) The data needs of activity scheduling models. Presented at the International Conference on Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, May.

Axhausen, K.W. and T. Gärling (1992) Activity-based approaches to travel analysis: Conceptual frameworks, models, and research problems. *Transport Reviews*, 12(4), 323-341.

Beckman, R.J., K.A. Baggerly and M.D. McKay (1995) Creating Synthetic Baseline Populations. LA-UR 95-1985, Los Alamos National Laboratory, Los Alamos, New Mexico

Bhat, C.R. (1996a) A hazard-based duration model of shopping activity with nonparametric baseline specification and nonparametric control for unobserved heterogeneity. *Transportation Research* (forthcoming).

Bhat, C.R. (1996b) A generalized multiple durations proportional hazard model with an application to activity behavior during the evening work-to-home commute. *Transportation Research* (forthcoming).

Bhat, R.C. and F.S. Koppelman (1993) A conceptual framework of individual activity program generation. *Transportation Research*, 27A, 433-46.

Bollen, K.A. (1989) *Structural Equations with Latent Variables*. Wiley, New York.

Chapin, F. S. (1978) Human time allocation in the City. In Carlstein, T., D. Parkes and N. Thrift (eds.) *Timing Space and Spacing Time: Human Activity and Time Geography*. Edward Arnold, London.

Damm, D. (1983) Theory and empirical results: a comparison of recent activity-based research. In S. Carpenter and P.M. Jones (eds.) *Recent Advances in Travel Demand*, Gower Publishing, Aldershot.

Ettema, D., A. Borgers and H. Timmermans (1993) Simulation model of activity scheduling behavior. *Transportation Research Record*, 1413.

Ettema, D., A. Borgers and H. Timmermans (1994) Using interactive computer experiments for identifying activity scheduling heuristics. Paper presented at the Seventh International Conference on Travel Behaviour, Valle Nevada, Santiago, June 13-16.

Ettema, D., A. Borgers and H. Timmermans (1995) A competing risk hazard model of activity choice, timing, sequencing and duration. *Transportation Research Record* (forthcoming).

Gärling, T., K. Brännäs, J. Garvill, R.G. Golledge, S. Opal, E. Holm and E. Lindberg (1989) Household activity scheduling. In *Transport Policy, Management and Technology Towards 2001: Selected Proceedings of the Fifth World Conference on Transport Research*, Vol. IV, Western Periodicals, Ventura, California, pp. 235-48.

Gärling, T. and J. Garvill (1993) Psychological explanations of participation in everyday activities. In T. Gärling and R.G. Golledge (eds.) *Behavior and Environment: Psychological and Geographical Approaches*, Elsevier Science Publishers, Amsterdam.

Gärling, T., M.-P. Kwan and R.G. Golledge (1994) Computational-process modelling of household activity scheduling. *Transportation Research B*, 28B(5), 355-364.

Golob, T.F. and M.G. McNally (1995) A model of household interactions in activity participation and the derived demand for travel. Presented at the Conference on Activity Based Approached: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, May 25-28.

Golob, T.F., M.A. Bradley and J.W. Polak (1996) Travel and activity participation as influenced by car availability and use. Presented at the 75-th Annual Meeting of the Transportation Research Board, Washington, D.C., January 7-11.

Hägerstrand, T. (1970) What about People in Regional Science? *Papers of the Regional Science Association*, 24, 7-21.

Hall, P. (1988) *Cities of Tomorrow*. Blackwell Publishers, Oxford.

Jones, P.M. (1983) The practical application of activity-based approaches in transport planning: An assessment. In S.M. Carpenter and P.M. Jones (eds.) *Recent Advances in Travel Demand Analysis*, Gower Publishing, Aldershot.

Jones, P. (1995) Contributions of activity-based approaches to transport policy analysis. Paper presented at the Workshop on Activity Analysis, Eindhoven, The Netherlands. May 25-28.

Jones, P.M., M.C. Dix, M.I. Clarke and I.G. Heggie (1983) *Understanding Travel Behaviour*. Gower Publishing, Aldershot.

Jones, P., F. Koppelman and J.P. Orfueil (1990) Activity analysis: State-of-the-art and future directions. In P. Jones (ed.) *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, Gower Publishing, Aldershot.

Kitamura, R. (1984) A sequential, history dependent approach to trip-chaining behavior. *Transportation Research Record*, 944, 22-38.

Kitamura, R. (1988) An evaluation of activity-based travel analysis. *Transportation*, 15, 9-34.

Kitamura, R. (1992) A review of dynamic vehicle holdings models and a proposal for a vehicle transactions model. *Infrastructure Planning and Management* (Proceedings of Japan Society of Civil Engineers), 440/IV-16,13-29.

Kitamura, R. (1995) Generation of Synthetic Daily Activity-Travel Patterns: Outline of the Approach. A report prepared for the National Institute of Statistical Sciences and Los Alamos National Laboratory, Institute of Transportation Studies, University of California, Davis, California.

Kitamura, R., J. Robinson, T.F. Golob, M. Bradley and T. van der Hoorn (1992), A Comparative Analysis of Time Use Data in the Netherlands and California: Effects of Commute Times and Store Operating Hours on Travel and Activity Patterns. Proceedings of Seminar E, 20th PTRC Summer Annual Meeting PTRC Education and Research Services Ltd., London, pp. 127-138.

Kitamura, R., C.V. Lula and E.I. Pas (1993) AMOS: An activity-based, flexible and truly behavioral tool for evaluation of TDM measures. *Proceedings of the 21st Summer Annual Meeting: Transportation Planning Methods*, PTRC Education and Research Services, Ltd., London, pp. 283-294.

Kitamura, R., R.M. Pendyala, E.I. Pas and P. Reddy (1995a) Application of AMOS, an Activity-Based TCM Evaluation Tool, to the Washington, D.C., Metropolitan Area. *23rd European Transport Forum: Proceedings of Seminar E Transportation Planning Methods*, PTRC Education and Research Services, Ltd., London, pp. 177-190.

Kitamura, R., T. van der Hoorn and F. van Wijk (1995b) A comparative analysis of daily time use and the development of an activity-based traveler benefit measure. Presented at the Conference on Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, May.

Kitamura, R. and S. Fujii (1996) Two computational process models of activity-travel behavior. To be presented at the Conference on Theoretical Foundations of Travel Choice Modeling, Stockholm, August.

Kitamura, R., S. Fujii and Y. Otsuka (1996) An analysis of induced travel demand using a production model system of daily activity and travel which incorporates time-space constraints. Presented at the Fifth World Congress of the Regional Science Association International, Tokyo, May.

Kitamura, R., E.I. Pas and S. Fujii (1996) Time use data for travel demand analysis: Toward the next generation of transportation planning methodologies. (In preparation).

Kitamura, R., E.I. Pas, C.V. Lula, T.K. Lawton and P.E. Benson (1996) The sequenced activity mobility simulator (SAMS): An integrated approach to modeling transportation, land use and air quality. *Transportation* (forthcoming).

Kurani, K.S. and R. Kitamura (1996) Recent Developments and the Prospects for Modeling Household Activity Schedules. A report prepared for the Los Alamos National Laboratory, Institute of Transportation Studies, University of California, Davis, California.

Mannering, F., E. Murakami and S.-G. Kim (1993) Temporal stability of travelers' activity choice and home-stay duration: Some empirical evidence. Mimeograph.

Maslow (1970) *Motivation and Personality.* Harper and Row, New York.

Newell, A. and H.A. Simon (1972) *Human Problem Solving*. Prentice-Hall, Engelwood Cliffs, New Jersey.

Niemeier, D.A. and J.G. Morita (1996) Duration of trip-making activities by men and women: A survival analysis. *Transportation* (forthcoming).

Otsuka, Y. (1996) Development of a Simulation Model System of Activity and Travel Which Represents the Individual's Decision Process. Unpublished M.S. thesis, Department of Applied Systems Engineering, Kyoto University, Kyoto (in Japanese).

Pas, E.I. (1988) Weekly travel-activity behavior. *Transportation*, 15, 89-109.

Pas, E.I. and A.S Harvey (1991) Time use research and travel demand analysis and modeling. Presented at the Sixth International Conference on Travel Behavior. October, 18.

Pendyala, R.M., R. Kitamura and D.V.G. Prasuna Reddy (1995) A rule-based activity-travel scheduling algorithm integrating neural networks of behavioral adaptation. Paper presented at the Conference on Activity Based Approaches: Activity Scheduling and the Analysis of Activity Patterns, Eindhoven, May.

RDC, Inc. (1993) Further Comparative Analysis of Daily Activity and Travel Patterns and Development of a Time-Activity-Based Traveler Benefit Measure. Final report prepared for Ministerie van Verkeer en Waterstaat, Directoraat-Generaal Rijkswaterstaat, Rotterdam, the Netherlands. San Francisco, California, October.

RDC, Inc. (1995) Activity-Based Modeling System for Travel Demand Forecasting. A Travel Model Improvement Program (TMIP) final report prepared for Metropolitan Washington Council of Governments, Washington, D.C. San Francisco, California, August.

Recker, W.W., M.G. McNally and G.S Root (1986a) A model of complex travel behavior: Part 1: Theoretical development. *Transportation Research*, 20A(4), 307-18.

Recker, W.W., M.G. McNally and G.S. Root (1986b) A model of complex travel behavior: Part 2: An operational model. *Transportation Research*, 20A(4), 319-30.

Root, G.S and W.W. Recker (1983) Toward a dynamic model of individual activity pattern formulation. In Carpenter, S. and P. Jones (eds.) *Recent Advances in Travel Demand Analysis*, Gower Publishing, Aldershot.

Tasker, M.P. and K.W. Axhausen (1994) DynaMIT: A Travel Behaviour Simulation Using Satisficing Search Methods. University of London Centre of Transport Studies, Imperial College of Science, Technology and Medicine, London.

Tonn, B.E. (1984a) A sociopsychological contribution to the theory of individual time-allocation. *Environment and Planning A*, 16, 201-223.

Tonn (1984b) The cyclic process decision-heuristic: An application in time-allocation modeling. *Environment and Planning A*, 16, 1197-1220.

Vause, M. (1995) A behavioural rule-based model of activity chains generation and scheduling. Presented at the Conference on Activity Based Approaches. Eindhoven, The Netherlands. 25-28 May.

Weiner, E. (1992) Urban Transportation Planning in the United States: An Historical Overview. Revised edition, DOT-T-93-02, U.S. Department of Transportation, Washington, D.C., November.

Weiner, E. (1993) Upgrading travel demand forecasting capabilities. Paper presented at the Fourth National Conference on Transportation Planning Methods Applications, Daytona Beach, Florida.